

Article

Explainable Shape Anomaly Detection of Space Targets from ISAR Image Sequences

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Highlights

What are the main findings?

- An explainable shape anomaly detection model combining A Fully Convolutional Data Description(FCDD) network with an attention-based GRU ensures abnormal detection of ISAR image sequences.
- By highlighting abnormal distribution through the Fully Convolutional Data Description(FCDD) network and enhancing the ability of extracting temporal features via the attention-based GRU, the model's detection performance is elevated.

What is the implication of the main finding?

- This approach enhances the abnormal detection performance under conditions of insufficient abnormal samples.
- It provides a robust solution to detect and locate the abnormal shape of spatial targets.

Abstract

Shape anomaly detection of satellites is critical to ensuring their safe operation. With the intrinsic range-Doppler projection mechanism, the inverse synthetic aperture radar (ISAR) image sequence has a high potential for localizing and detecting satellites' shape anomalies. In this manuscript, we propose a Fully Convolutional Data Description (FCDD) joint temporal sequential classification network to extract both spatial and temporal information for shape anomaly detection of space targets. The explainable FCDD network is initially built to generate explainable heatmaps of anomalies. An attention-based GRU is used to learn context information between heatmap sequences by converting detection into sequential binary classification. In this way, the joint temporal and spatial information extraction proposal can not only detect shape anomalies with high precision and low false alarm rate but also retain the capability of generating explainable heatmaps to localize satellite shape anomaly components. Extensive experimental results confirm the superiority of the proposal.

Keywords: space target; shape anomaly; anomaly detection; ISAR sequences



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1. Introduction

Detection is a critical task in space situational awareness [1,2]. On-orbit satellites with various payloads and subsystems frequently experience inevitable component failure due to severe temperatures and electromagnetic radiation. Space target anomalies can generally

be divided into three categories: orbit transfer, attitude anomaly, and shape anomaly [3,4]. The detection of the first two aberrant occurrences has been extensively researched in recent years [5–10]. However, the shape anomaly detection for space targets remains a relatively unexplored field. Like other anomaly events, shape anomaly detection can help find unanticipated flaws in components' shape and save them in time. For example, in October 2006 and February 2007, both the test Beidou navigation satellite and Sinosat-2 encountered solar wing unfolding problems [11,12]. In June 2024, the disintegration of Russia's RESURS-P1 satellites produced 100 debris, which posed a great threat to the International Space Station [13]. Therefore, it is particularly important to detect these shape anomalies of satellites as soon as possible, which can help monitor space targets and react in time.

The high-resolution inverse synthetic aperture radar (ISAR) has been a prominent sensor in long-term space target surveillance due to its long distance, all-day, all-weather capabilities and high revisit frequency [14–16]. Generally speaking, ISAR can provide a series of high-resolution images in the range and azimuth directions to portray the fundamental shapes of satellites. However, ISAR's unique electromagnetic imaging method makes robust shape extraction problematic due to incomplete edges, excessive glint scatters, and speckle noise. Therefore, the utilization of ISAR images to detect shape anomalies for space targets is important but challenging.

The shape anomaly detection of satellites from ISAR images can be considered as an anomaly detection (AD) of images in industrial fields. Basically, AD is an operation that measures a sample's deviation from the established dataset's norms. Typically, this assignment involves distinguishing between 'normal' and 'anomalous' using the binary classification paradigm [17]. AD methods can be classified as unsupervised, semi-supervised, or supervised learning approaches. Unsupervised AD techniques are particularly valuable in scenarios where there is a shortage of labeled data. Anomaly detection can be achieved by automatically learning the feature distribution of normal data samples and identifying examples that deviate from the learned distribution. This umbrella encompasses traditional approaches such as the Isolation Forest [18] and One-Class SVM (OCSVM) [19]. The isolation forest identifies anomalies by isolating observations from a randomly partitioned feature space. OCSVM, on the other hand, is intended for unsupervised outlier detection by calculating the support of a high-dimensional distribution. In recent years, there has been a surge of interest in developing a novel deep learning technique, especially for AD. These advanced methodologies harness the power of neural networks to learn from data directly. Ref. [20] employs the autoencoder to accurately rebuild normal data samples while struggling with anomalous samples. The resulting reconstruction error is then used to calculate an anomaly score [21]. However, one of the most effective AD methods is based on supervision, which trains a network to predict an anomaly score based on the confidence level of the predictions by including known anomalies into the training process [22,23]. With enough abnormal data, such methods are especially effective because they may learn from the intricacies of both normal and anomalous data, resulting in more accurate and robust AD systems. Yet, creating a comprehensive dataset that includes all potential departures from normalcy is a daunting task. Since the supplied anomalies cannot fully represent "anomalousness," semi-supervised anomaly detection appears to offer a promising approach. These methods incorporate auxiliary anomalous data to enhance the performance of unsupervised classification methods that are trained on nominal data [24]. These methods aim to separate nominal samples from anomalies in an unsupervised manner, effectively concentrating nominal data in feature space and mapping away anomalies [25]. Although there is much recent research on ADs, there is limited work on making them explainable.

However, explainable AD are especially critical for space targets to meet safety and security standards, prevent unfair social biases, and aid human decision-making [26–28]. We care not only whether AD occurs but also where it occurs. In this way, we can help rescue high-value space targets in time. To address the issue of explainability, various strategies have been introduced throughout the years [29]. Many of these methods, including reconstruction errors [30], attention learning [31], and gradient back-propagation [32], can be used or adapted to provide well-explainable detection results. A Fully Convolutional Data Description (FCDD) network has been proposed as one method for producing a down-sampled anomaly heatmap [33]. This heatmap uses solely convolutional and pooling layers to identify pixels that vary significantly from the anomalous center. The FCDD's AD performance is comparable to the best available AD methods on established benchmarks such as CIFAR-10 and ImageNet [33]. Building on this, our paper explores a modification of the FCDD to achieve explainable shape anomaly detection based on ISAR image sequences.

For satellite AD, data-driven fault diagnosis techniques have gained popularity recently. Most of this research has been focused on detecting anomalies with satellite housekeeping data [34–37]. For instance, Zeng et al. [34] introduced a CN-FA-LSTM anomaly detection approach that can identify subtle patterns and detect abnormalities with high accuracy. A satellite health monitoring system that incorporates probabilistic clustering and dimensionality reduction techniques has been proven to have outstanding impacts on telemetry datasets [37]. Additionally, there is an emphasis on detecting dynamic abnormalities in space targets. By considering the micro-Doppler-related features or images, an anomaly detection algorithm based on the Gaussian mixture model (GMM) was proposed to identify the abnormal motion statuses of space targets in [38]. Furthermore, we proposed a framework that integrates the sparse constraint with LSTM to detect abnormal dynamic status from ISAR sequences in ref. [7]. For shape anomaly detection of space targets, such as solar panel unfolding, components detaching, and even disintegration, there is still little publicly available literature.

As a result, in this manuscript, we propose a framework for detecting shape anomalies in space targets utilizing ISAR image sequences, where sequential ISAR imaging of a specific space target is always generated for long-term surveillance during one circle. Given the imaging projection process of sequential ISAR, the projected feature flow of space targets in the ISAR image sequence exhibits a high potential for shape anomaly detection. In this way, we propose a temporal FCDD structure in this manuscript, known as FCDD-GRU-Att, to improve the single frame-based shape anomaly detection of satellites. The state-of-the-art interpretable FCDD architecture is used to generate anomalous heatmap sequences from ISAR sequences to aid in the interpretation of anomalous images, followed by an attention-based GRU structure to capture context relations between these interpretable heatmap sequences. By incorporating of temporal and geographical features, the shape AD performance has been significantly boosted through experiments. Furthermore, by up-sampling the heatmap sequences to the image size, our proposal can not only demonstrate how the anomalous images differ from the norm, but it can also pinpoint the anomalous parts in ISAR images. Compared to available AD methods for satellites, the novelty of the proposal can be concluded as follows:

- (1) To the best of our knowledge, this is the first paper to suggest employing an ISAR image sequence to detect shape anomalies in space targets. On one hand, ISAR images have the advantage of high-resolution, all-day, all-weather, and long-distance monitoring of uncooperative targets over low-resolution micro-Doppler data and cooperative housekeeping data. The existing literature, on the other hand, primarily focus on overall operations with housekeeping data or dynamic state monitoring

using ISAR and micro-Doppler data. Public research on satellite shape anomalies is notably lacking.

- (2) In this work, we introduce a novel framework that leverages spatial and temporal information to detect shape anomalies in image sequences for satellites. By constructing a joint structure of FCDD and attention-based GRU, we can considerably improve shape anomaly performance using both spatial and contextual information, thanks to the sequential imaging operation of space targets in long-term surveillance.
- (3) We propose an interpretable architecture for shape anomaly detection in satellite ISAR image sequences. This architecture not only enables the detection of anomalous frames but also allows for the precise localization of the erroneous components inside the associated ISAR image frames. This architecture can aid in a better understanding of AD results and offer a robust result for human decision-making.

The following contents of the paper are organized as follows: In Section 2, the ISAR sequential imaging projection is modeled, in which the geometrical feature sequence is proven to be effective in shape anomaly detection. In Section 3, the proposed FCDD-GRU-Att architecture is constructed for identifying abnormal shape anomalies of space targets in detail. Section 4 exhibits the experimental effectiveness of the proposal. Finally, some conclusions are given.

2. Sequential ISAR Imaging Geometry of Space Target

2.1. Sequential ISAR Imaging

In this manuscript, we assume that sequential ISAR images are generated using the equal accumulated imaging time premise. The sequential projection of ISAR in terms of the target cartesian coordinate is illustrated in Figure 1. The target cartesian coordinate is defined as follows: the x -axis points to the Earth's core, the y -axis is tangent to the target orbit, and the z -axis represents the object's motion plane's normal vector.

As a result, the light of sight (LOS) of ISAR $\vec{k}$ can be described by elevation and azimuth angles (θ, ϕ) in a target coordinate, such as

$$\vec{k} = [\cos \theta(t_m) \sin \phi(t_m), \cos \theta(t_m) \cos \phi(t_m), \sin \theta(t_m)]^T \quad (1)$$

where t_m is the slow time.

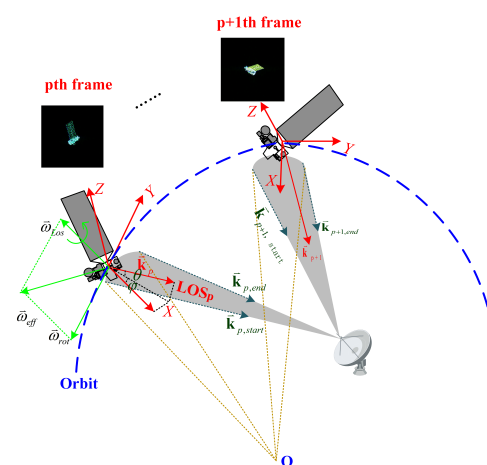


Figure 1. ISAR imaging geometry of satellites.

ISAR imaging is a process that projects a 3D target onto a 2D imaging plane. The 2D imaging plane is defined by two orthogonal coordinate unit vectors $\vec{r}$ and $\vec{F}_d$. The range

direction $\vec{r}$ is the LOS direction, and the Doppler direction $\vec{F}_d$ is defined by the effective rotation vector $\vec{\omega}_{eff}$, such as

$$\vec{F}_d = \frac{\vec{k} \times \vec{\omega}_{eff}}{\|\vec{k} \times \vec{\omega}_{eff}\|} \quad (2)$$

where $\times$ denotes the outer product of two vectors. For on-orbit space targets, the effective angular velocity $\vec{\omega}_{eff}$ is a combination of orbit motion and self-rotation as

$$\vec{\omega}_{eff,p} = \vec{\omega}_{LOS,p} - \vec{\omega}_{rot,p} \quad (3)$$

where $\vec{\omega}_{rot,p}$ and $\vec{\omega}_{LOS,p}$ denote self-rotation angular velocity and the intersection direction between the start and end LOS vector in an imaging frame, such as

$$\vec{\omega}_{LOS,p} = \left\langle \vec{k}_p(t_0), \vec{k}_p(t_0 + CPT) \right\rangle / CPT \quad (4)$$

where CPT represents the coherent processing time for each imaging frame under constant acceleration.

As previously noted, because of ISAR's peculiar scattering process, angular glint makes the point feature fragile. We recommend using the robust skeleton feature instead of point features to illustrate satellite shape differences. As illustrated in Figure 2, the skeleton can be defined by two perpendicular vectors. The vectors can be described using projected lengths R_i and d_i in the RD imaging plane.

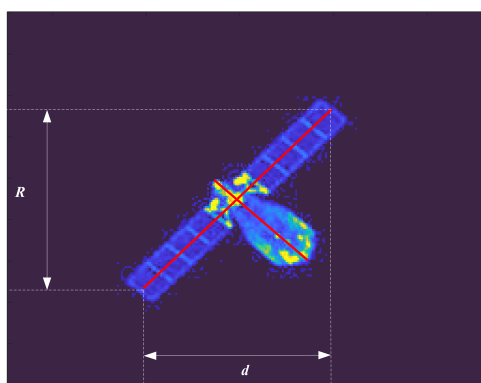


Figure 2. Shape description of satellite in ISAR images.

By the RD imaging projection, the projected length of main axis in range direction R can be written as

$$\begin{aligned} R &= \vec{k}_{\text{Radar},R} \cdot \vec{l} \\ &= L \begin{pmatrix} \cos \theta \sin \phi \cos \alpha \sin \beta + \\ \cos \theta \cos \phi \cos \alpha \cos \beta + \sin \theta \sin \alpha \end{pmatrix} \end{aligned} \quad (5)$$

where $\vec{l} = L[\cos \alpha \sin \beta, \cos \alpha \cos \beta, \sin \alpha]^T$ defines the primary axis of space target in the target coordinate, L stands for its length, α and β denote the direction of the vector, which is defined similarly to θ and ϕ .

The projected length in azimuth is denoted as d , which can be written as

$$d = \omega_{eff} \vec{F}_d \cdot \vec{l}. \quad (6)$$

2.2. Sequential ISAR Image of Satellite Shape Anomalies

Shape anomalies in satellites are characterized as abnormal phenomena in their appearance that introduce variations in geometry, texture, and so on. Typical shape anomaly phenomena include solar panel folding, satellite fragmentation, jammer attachment, and so on.

In this paper, we concentrate on shape anomalies that can introduce geometrical changes in ISAR images. As previously indicated, we defined the basic geometry of satellites as two perpendicular major axes. Here, we will model the changes of the two vectors in shape anomaly events across distinct dynamic states. The shape-represented vectors in the imaging plane are illustrated in (5) and (6). Once a shape anomaly occurs, the length L will change to L' , such as

$$R_a = L' \begin{pmatrix} \cos \theta \sin \phi \cos \alpha \sin \beta + \\ \cos \theta \cos \phi \cos \alpha \cos \beta + \sin \theta \sin \alpha \end{pmatrix} \quad (7)$$

$$\begin{aligned} d_a &= \omega_{eff} \vec{F}_d \cdot \vec{l} \\ &= L' \omega_{eff} \left[\frac{(\vec{\omega}_{eff} \times \vec{k})}{\|\vec{\omega}_{eff} \times \vec{k}\|} \cdot [\cos \alpha \sin \beta, \cos \alpha \cos \beta, \sin \alpha]^T \right] \end{aligned} \quad (8)$$

As a result, in the anomalous imaging frame, an abrupt shift in projected length R_a and d_a will be shown, followed by successive changes in different states. In general, the LOS-defined θ and ϕ can be considered to rotate at a constant angular velocity. For three-axis stabilized space targets, α and β are constants. As a result, with the ISAR image sequence of three-axis stabilized satellites, the projected range R will fluctuate in proportion to θ and ϕ . When a space target moves itself, its position changes in the target coordinate. That indicates α and β change with time. The projected range R will be determined by the combined changes in (θ, ϕ) and (α, β) as (7).

For three-axis stabilized space targets, $\vec{\omega}_{eff,p}$ only comes from the rotation of LOS as (3). According to ref. [7], the azimuth resolution of stably managed space targets will adhere to the regulation from low to high and back to low, which corresponds to the on-orbit motion from low to high to low elevation. When a space target rotates, the effective rotation is caused by both the rotation of LOS and the target itself. When the rotation velocity is double that of LOS, the rotation itself is mostly responsible for the effective rotation. In this manner, the azimuth resolution will remain consistent throughout the imaging series.

In summary, the shape anomaly will cause rapid changes in the projected lengths and directions of the main axes of space targets in the imaging frame. The projected azimuth length then changes, as it did in its dynamic states. As a result, the shape sequences of space targets may be utilized for shape anomaly detection, which is the motivation behind our proposal.

For clarity, a simulated 400 km high satellite is spotted from Beijing station (39.9°N, 116.4°E, 0 m) using TLE parameters acquired from the tracking system, as shown in Figure 3a,b. The projected lengths R and d of primary axes in different dynamics (normal or abnormal) and shape states (normal or abnormal) are shown in Figure 3c,d. Clearly, the shape anomalies will introduce sudden changes in projected lengths, whatever the dynamic states of the satellites are. Afterwards, the projected lengths will follow the change of its dynamic states.

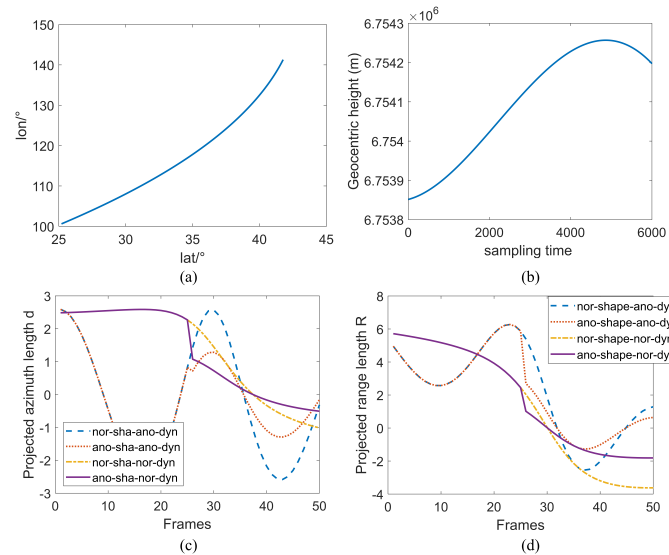


Figure 3. ISAR sequential shape changes in different dynamics. The nor-sha-ano-dyn denotes the targets with anomalous dynamics but have a normal shape. The ano-sha-ano-dyn denotes the targets with anomalous dynamics and have an abnormal shape. The nor-sha-nor-dyn denotes the targets that have normal shape and normal dynamics. The ano-sha-nor-dyn denotes the targets which are of abnormal shape but have normal dynamics. (a) Longitude vs Latitude; (b) Geocentric height of the space target (target to the earth's core); (c) Projected azimuth length change in different shapes and dynamic states; (d) Projected range length change in different shapes and dynamic states.

3. Sequential Shape Anomaly Detection of Space Targets

3.1. FCDD Network [33]

Here, we begin by introducing the explainable anomaly detection architecture, the Fully Convolutional Data Description (FCDD), which yields an anomalous shape-related heatmap sequence. The FCDD network is a deep one-class approach that employs the fully convolutional network (FCN) and hypersphere classifier (HSC). As shown in Figure 4, the FCDD is composed of three main structures.

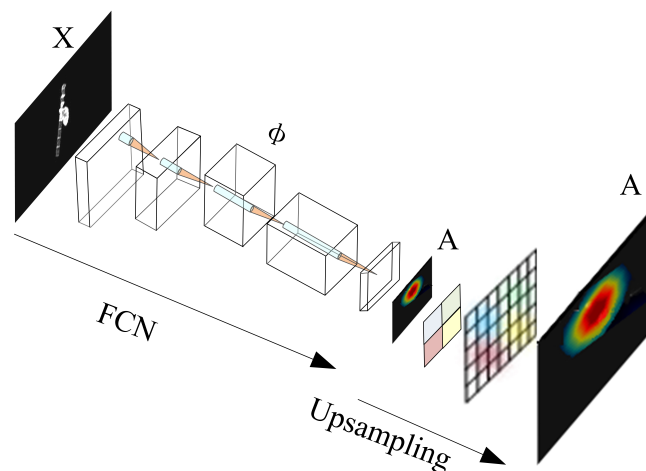


Figure 4. Visualization of the overall procedure of FCDD to produce anomaly heatmaps.

FCN: The FCN converts an ISAR image into a feature matrix using convolution and pooling. Here, we utilize the VGG-16 backbone network because of its high classification efficiency.

Geometrical regulation: The FCN output $\phi(X, \omega)$ is then regulated by the geometrical enhanced function $A(X) = \left[\sqrt{\phi(X, \omega)^2 + 1} - 1 \right]$, which outperforms other geometry regulations such as l_1 , l_2 , and l_2^2 in anomaly detection [39].

Heatmap Up-sampling: In reality, it is hard and time-consuming to collect ground-truth pixel annotations for anomalous samples. Therefore, FCDD proposes up-sampling $A(X)$ using a transposed convolution with a fixed Gaussian kernel to generate anomalous heatmaps of the same size as the input ISAR image.

The FCDD objective function is specified by the pseudo-Huber loss on the up-sampling heatmap, such as

$$\min_{\omega} \left\{ \begin{array}{l} \frac{1}{n} \sum_i (1 - y_i) \frac{1}{hw} \|A'(X_i)\|_1 \\ -y_i \log \left(1 - \exp \left(-\frac{1}{hw} \|A'(X_i)\|_1 \right) \right) \end{array} \right\} \quad (9)$$

where $X_1, X_2, \dots, X_n$ are ISAR images, y_i denotes the labels with anomalies $y_i = 1$ and nominal $y_i = 0$, h and w determine the input ISAR image's original dimensions, and $A'(X_i)$ is the parameter for up-sampling $A(X)$.

3.2. Sequential Shape Anomaly Detection Network

Shape anomalies in different dynamics may be detected using shape sequences of ISAR images, as explained in Section 2.2. As a result, we utilize an FCDD-generated heatmap sequence to describe shape fluctuations. The ISAR sequence-based shape anomaly detection problem can then be transformed to a sequence-to-sequence binary classification problem. In this way, we propose a temporal FCDD network to identify sequential shape anomalies for ISAR images with attention-based GRU. The proposed sequential shape anomaly detection network is drawn in Figure 5.

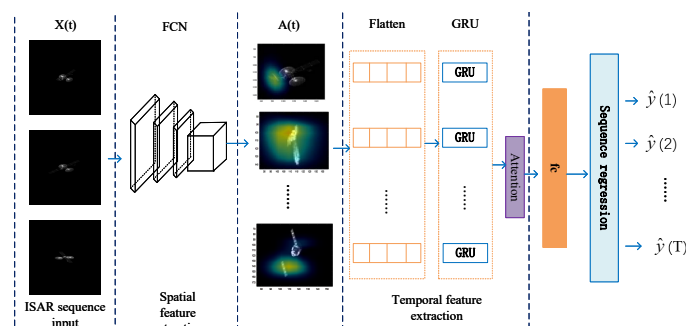


Figure 5. Visualization of the overall procedure of FCDD-GRU-Att network.

The proposal consists of three primary modules.

Spatial feature extraction: The first module extracts anomaly-related spatial features using the FCN and $A(X)$ in FCDD. In this way, a down-sampled anomaly heatmap sequence is generated as $A(1), A(2), \dots, A(T)$.

Temporal feature extraction: We propose extracting temporal features from anomalous heatmap sequences using GRU and temporal self-attention mechanisms. The attention-GRU model is proven effective in time-series data analysis [40].

GRU is a variant of a recurrent neural network that uses reset and update gates to manage the amount of historical information retained. The reset and update gates are computed as

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]), z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (10)$$

where x_t is the t th input of the sequence and h_{t-1} denotes the state at $(t - 1)$ th moment. The gates can regulate the amount of information utilized at this moment by using the

weight parameters W_r , W_z and activation function σ . The hidden state is updated according to (11):

$$h_t = (1 - z_t) \times h_{t-1} + z_t \tanh(W_{\tilde{h}} \cdot [r_t \times h_{t-1}, x_t]) \quad (11)$$

The attention mechanism operates by assigning different weights to information at different moments. Since different temporal input has varying degrees of importance at this point, we add an attention layer following the GRU layer. The attention mechanism functions as follows:

$$\tilde{H} = \text{softmax}\left(\frac{QK^T}{\sqrt{d_K}}\right)V \quad (12)$$

where $Q = X \times W_Q$, $K = X \times W_K$, $V = X \times W_V$, d_K denotes the number of columns in Q and K . Using the softmax function, the attention coefficients for each moment to other moments may be calculated. By multiplying V , the weighted temporal feature vector may be updated.

Sequence classification: Following spatial and temporal feature extraction, the sequential shape anomaly detection problem may be converted into a sequential classification problem with a loss function specified as

$$L = \sum \frac{1}{C} y_i \log(\hat{y}_i) \quad (13)$$

where $C = 2$ is the number of the shape classes, i.e., normal shape and anomaly shape, y_i and $\hat{y}_i$ are the one-hot representation and estimated probability, respectively.

Finally, Table 1 lists the comprehensive design of the sequential shape anomaly detection network FCDD-GRU-Att.

Table 1. Detailed parameter configuration of the sequential shape anomaly detection FCDD-GRU-Att network.

Module	Layers	Layer Type	Parameters
FCN	1–24th	Layer1–24 in VGG	
	25–30th	Convolutional layer $\times 2$	Filters = 512; Kernel size = 3; Stride = 1
		Batch normalization layer $\times 2$	Filters = 512
		Activation layer $\times 2$	ReLU
	31st	Convolutional Layer	Filters = 512; Kernel size = 1; Stride = 1
Geometrical Enhancement	32nd	$A(X) = [\sqrt{\phi(X, \omega)^2 + 1} - 1]$	
Sequential feature extraction	33rd	Flatten layer	—
	34th	GRU	128 GRUs
	35th	Self-attention	4 Heads Q,K,V channel = 256
Classification	36th	Fully connected	—
	37th	Classification	

Training data and labels: The sequential shape anomaly detection FCDD-Attention-based GRU network is trained on consecutive samples labeled as nominal or anomalous. Let $\{X_1(t), \dots, X_n(t)\}$, $t = 1, 2, \dots, T$ denote a collection of sequential samples with labels $\{y_1(t), \dots, y_n(t)\}$.

Training tricks: As illustrated in ref. [27], the FCDD network may perform remarkably well with a small corpus of labeled anomalies. Therefore, we may initially train the FCDD network with a single-frame ISAR image dataset. The proposed FCDD-GRU-Att network may converge quickly by fine-tuning the temporal feature extraction module after transferring the FCDD-trained parameters.

4. Experiments and Analysis

In this section, several experiments are performed to validate the effectiveness of the suggested sequential shape anomaly architecture. First, the dataset is created. Second, the FCDD network is proven to identify shape anomalies in single-frame ISAR images. Afterward, the proposed FCDD-GRU-Att network is conducted to a simulated sequential ISAR image dataset. Then, the bounds of the proposal are reviewed under various conditions, such as training anomaly quantities, frame number per sequence, and SNR. Finally, comparisons are performed to establish the proposal's superiority.

4.1. Introduction of Experimental Data

Before we begin, a brief introduction to the simulated dataset used in this experiment is provided for clarity. Due to the lack of real measured satellite ISAR images with shape anomalies, the proposal is examined with simulated ISAR data.

- (1) ISAR image generation: Because of a paucity of real data, our experiments are conducted on simulated data of different satellites. Six distinct satellites are used, and the 3D point models are depicted in Figure 6. The improved physical optical (PO) algorithm is utilized for ISAR echo simulation, which has been proven to be effective for the majority of satellite echo generation [41]. Table 2 lists the simulated parameters of a Ku-band radar for clarity. For data diversity, two different ground stations are constructed for simulation, located in Beijing (39.9°N, 116.4°E) and Tianjin (39.1°N, 117.2°E). The real-measured TLEs are adopted for satellite orbit description. An example of TLE is shown in Figure 3a,b. The traditional RD imaging algorithm is used to generate ISAR images. Examples of simulated ISAR images for different targets are shown below their 3D point model.

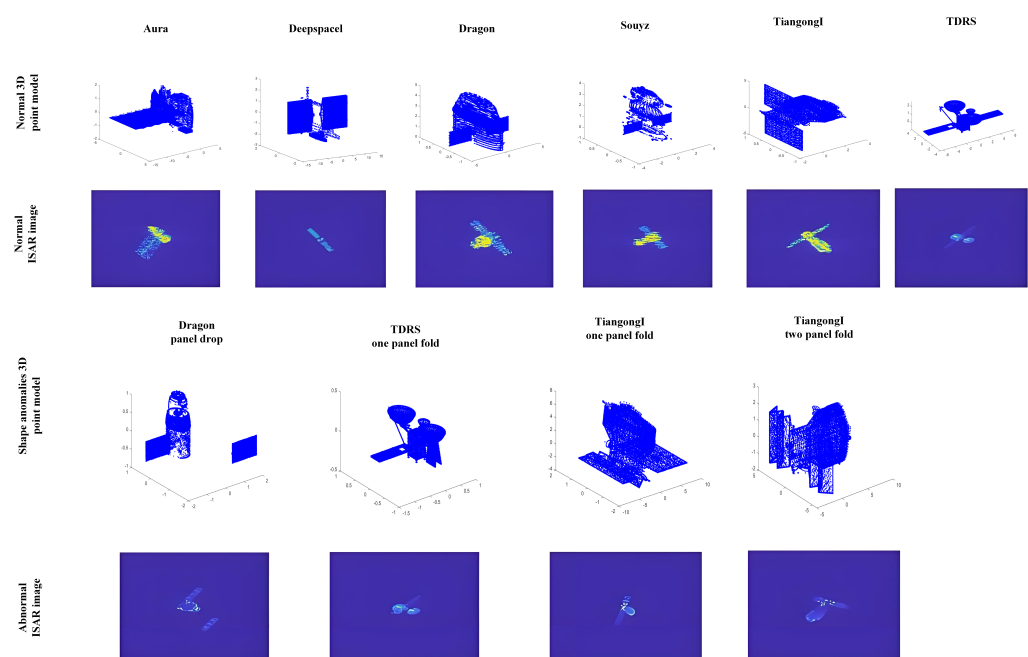


Figure 6. Illustration of a 3D point model and simulated ISAR images in normal and abnormal shapes. The first row shows the 3D point, the second row illustrates the corresponding ISAR images in normal shape, the third line shows the 3D points of shape anomaly satellites, and the fourth line shows the corresponding ISAR image in normal shape.

Table 2. Main parameters of the ISAR System.

Parameter	Value
Center frequency	15 GHz
Bandwidth	1.5 GHz
Coherent Processing Time	0.6 s
Imaging Time Interval	10 s
Image size	225 × 225
Frame rate	30 Hz

Afterwards, the equal accumulation time model is used to construct the ISAR sequences to ensure phase consistency between frames. Diverse initial attitudes are generated for each sequence to result in different attitudes. According to Table 2, the coherent time for imaging is 0.6 s, and the interval between each imaging frame is 10 s. Eventually, an ISAR image sequence of 36 frames is generated for each lap.

- (2) Generation of different dynamic status: For the diversity of data, we also simulate satellites in a variety of dynamic statuses, including three-axis stability, self-rotation, and attitude adjustment within one frame. The rotation velocity is set as $0.1^\circ/\text{s}$ and $1^\circ/\text{s}$ for the last two statuses. For each orbiting circle, 30 frames of ISAR images with a 10 s interval are generated for sequential shape anomaly detection performance evaluation.
- (3) Evaluate criterion: Same as detection problems, the fundamental criterion for anomaly detection that we care about is the detection capabilities under specific false alarm rates. As a result, overall precision (Prec), detection rates (Detec), and false alarm rates (FA) are computed for quantitative assessments, whose definitions are given as

$$\begin{aligned}
 \text{Precision} &= \frac{TP + TN}{TP + TN + FP + FN} \\
 \text{Detec} &= \frac{TP}{TP + FP} \\
 \text{FA} &= \frac{FN}{FN + TN}
 \end{aligned} \tag{14}$$

True anomalies are denoted as TP, true normal samples as TN, false detected anomalies as FP, and false detected normal samples as FN. For classification, they are the elements of a binary classification confusion matrix.

4.2. FCDD for One-Frame Shape Anomaly Detection

In this subsection, we conduct the FCDD for shape anomaly detection on a single ISAR image to validate its effectiveness in detecting and localizing anomalous parts.

Dataset: We simulated 3180 frames of normal ISAR images as well as 1860 ISAR images with shape anomaly for shape anomaly detection. We randomly choose 1650 normal images and 840 abnormal images for training, 360 normal images and 240 abnormal images for threshold calculation, and 1170 normal images and 780 anomalies for testing. This experiment includes typical abnormal shape phenomena, such as single sail folding, double sail folding, and sail detachment and disintegration. The training dataset and calculation dataset are constructed with more normal images than anomalies to imitate a lack of anomalies in real-world scenarios.

Training settings: After feeding the training samples into the constructed FCDD architecture, the training progress can be converged. The Adam solver is used with a 0.0001 learning rate and 0.9 gradient decay factor. The batch size is set to 200.

Anomaly score threshold computation: For FCDD shape anomaly detection, a calculation dataset should be constructed to calculate the anomaly-score-based threshold to discriminate normal images from shape anomalous ISAR images of satellites. Given the labels and scores of calculation samples, the threshold is determined by maximizing the difference between true positive rate (TPR) and false positive rate (FPR), as Figure 7 shows. The anomaly score threshold is computed as 0.726 in this way.

For clarity, the confusion matrix is given in Figure 8. Clearly, the FCDD is capable of detecting shape anomalies at 85.26% with 2.9% false alarms.

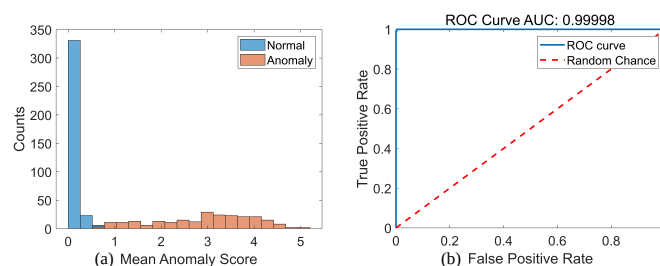


Figure 7. Anomaly score statistics. (a) Histogram of anomaly score; (b) ROC curve of anomaly scores.

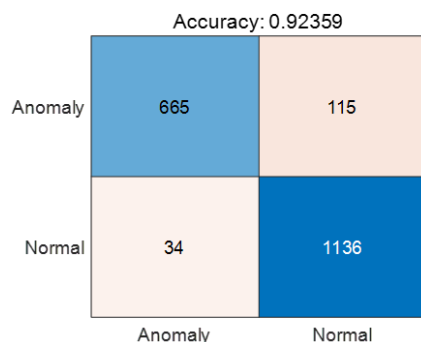


Figure 8. Confusion matrix of FCDD for shape anomaly detection.

Moreover, one advantage of FCDD is that it provides explainable descriptions of anomalies. Therefore, we randomly selected up-sampled heatmaps from TP, TN, FP, and FN samples to validate the effectiveness of anomaly explanations, as shown in Figure 9. As demonstrated, FCDD can not only detect but also pinpoint shape-anomalous parts in satellites. There are two significant false cases. First, the FPs and FNs exhibit low anomaly scores close to the threshold. As shown, normal images and anomalies have overlapping mean anomaly scores ranging from 0.5 to 1. Otherwise, they are hardly recognized in images such as FP 2, 3, 5, and FN 1, 2, 3.

To further evaluate the quality of FCDD, histograms of TP, TN, FP, and FN are plotted in Figure 10a. As shown, anomaly scores of FPs are primarily concentrated around the threshold. FNs mainly receive low scores because of observed attitude-induced failures in satellite structure integrity description. In this way, geometrical features of satellites in ISAR images have been proven to make a difference in shape anomaly detection. Figure 10b plots the false rates of different targets. The FP mainly comes from the detection of one solar panel fold of TDRS and Tiangong. The FN has the same cases.

Clearly, fixed threshold-based shape anomaly detection cannot distinguish between situations with low anomaly scores. In this way, we propose to utilize the sequential ISAR images to improve shape anomaly detection performance by exploiting context relations between frames. By converting the sequential detection into a sequential binary classification problem, most misjudged abnormal anomaly cases can be corrected by utilizing temporal information.

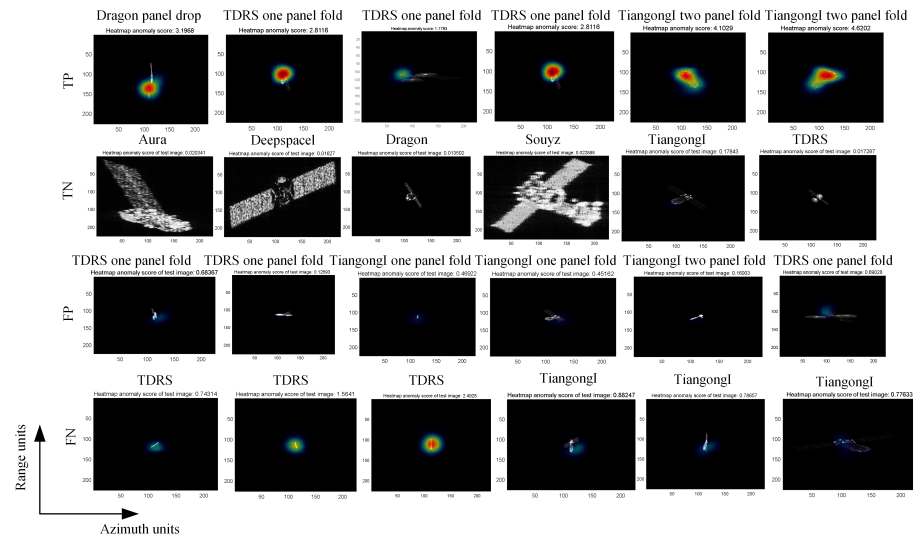


Figure 9. FCDD explanation heatmaps for satellite ISAR images. The **first row** shows TPs of different targets, the **second row** illustrates TNs of different targets, the **third row** shows FP, and the **last row** gives FN samples.

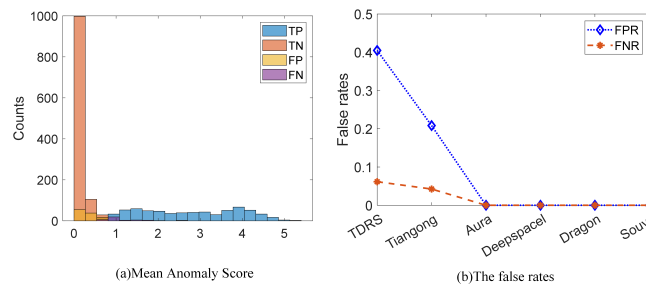


Figure 10. Anomaly score statistics. (a) Anomaly score histograms; (b) False alarm rates of different targets.

4.3. Sequential Shape Anomaly Detection for ISAR

In this subsection, we bring in the temporal features to improve the performance of shape anomaly detection. The architecture of the proposed FCDD-GRU-Att is listed in Table 1.

Dataset: For comparison, we utilized the same dataset of single frames. Each observed orbit has 30 frames for sequential shape anomaly detection. FCDD-GRU-Att just uses training and testing datasets because threshold calculation is not required.

Training settings: After feeding the training sequential samples into the FCDD-GRU-Att network, the training progress can be converged. The Adam solver is utilized with a 0.0001 learning rate.

Sequential shape anomaly detection: Instead of feeding a single frame ISAR image into a trained network, we explore both the temporal and spatial information in an ISAR sequence to improve shape anomaly detection properties. The trained FCDD parameters are used to initialize the same layers, accelerating the convergence of training progress in the proposed FCDD-GRU-Att architecture.

Using the same test dataset as in B, the confusion matrix of FCDD-GRU-Att is shown in Figure 11 after converting a single frame into 30-frame sequences. As illustrated in Figure 12a, the accuracy of shape status classification has been significantly improved by incorporating the temporal inertia of shape anomalies. The missed detection comes from a single sequence observation of the TDRS satellite. For clarity, we plot the anomaly score of a sequence that was incorrectly classified in FCDD but is correctly classified in FCDD-GRU-Att in Figure 12b. As shown, anomaly scores may be low in single frames, resulting in

false judgment inevitably for FCDD. However, by introducing context information in real time, detection can be significantly improved. Therefore, the introduced FCDD-GRU-Att architecture can identify sequential shape anomalies with high quality.

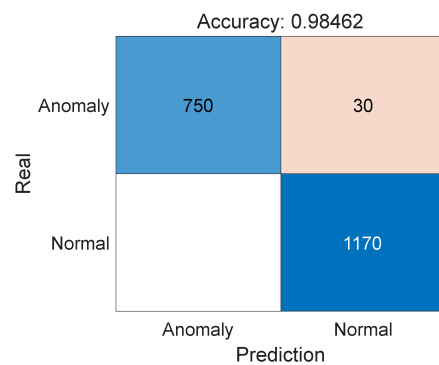


Figure 11. Confusion matrix of FCDD-GRU-Att.

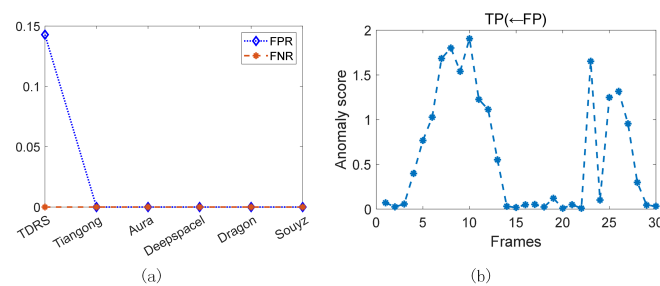


Figure 12. Performance evaluation of FCDD-GRU-Att. (a) False rates of different targets; (b) Anomaly scores of a sequence from FPs to TPs.

Moreover, the proposal can provide explanations like FCDD. Instead of using the Gaussian kernel to up-sample $A(X)$, we prefer nearest interpolation for simplicity. As illustrated in Figure 13, sequential shape anomaly detection can improve detection precision while also maintaining the explainable capability of FCDD.

To further illustrate the superiority of the proposed structure, we made certain structural alterations for comparison.

First, instead of feeding $A(X)$ into sequential classification, the anomaly score is used for comparison. Second, the GRU architecture is replaced by Bi-Lstm. Finally, the attention mechanism has been removed. For quantitative comparison, Prec, Detec, and FA are calculated. As shown in Table 3, the proposed structure is best suited for sequential anomaly detection for satellites using ISAR images, accounting for detection and false alarm rates. The A-Att-GRU denotes abnormal samples based on the GRU-Att architecture.

Table 3. Performance comparisons of different architectures.

Structures	Criteria	Prec (%)	Detec (%)	FA (%)
Score-Lstm		93.9	88.46	2.48
Score-Att-Lstm		96.92	96.15	2.56
A-Att-Lstm		96.92	93.23	0
A-GRU		91.80	81.28	1.2
A-Att-GRU		98.46	96.15	0

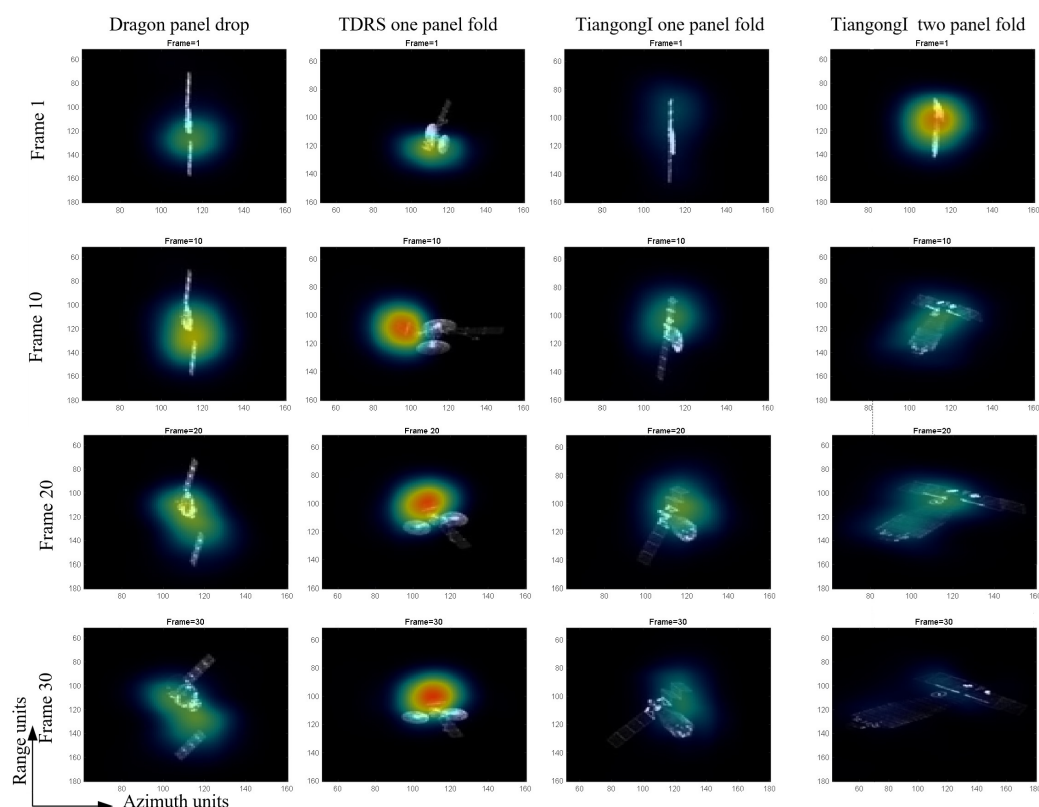


Figure 13. Explainable sequential heatmaps for satellite ISAR images of FCDD-GRU-Att.

4.4. Performance Evaluation Under Different Conditions

In this subsection, we will discuss the performance of the proposal under different conditions, including different anomaly amounts, different frame numbers of sequences, and different signal-to-noise ratios (SNRs).

Amounts of trained anomalies: In reality, the number of anomalies is not comparable to normality. Moreover, it is impossible to incorporate all cases of anomalies in the training process. Therefore, the anomaly detection problem cannot be solved solely through binary classification. The aims of anomaly detection methods are to maximize detection at low anomalous rates.

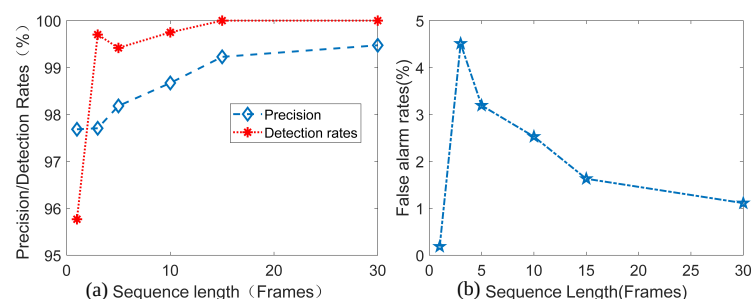
The training dataset in Section 4.1 includes 1650 normal images and 840 abnormal images. We gradually decrease the number of abnormal images from 840 to 600, 480, and 360 in turn. Meanwhile, the number of training normal images, calculation images, and testing images remains unchanged. There are four different shape-anomalous types with the observation sequence consists of 30 sequences. Therefore, the smallest number 360 represents only three sequences for each type of abnormality.

For comparison, FCDD is conducted to demonstrate the benefit of temporal information in anomaly detection. The precision, detection rates, and false alarm rates are computed for quantitative analysis. As shown in Table 4, the overall precision has been improved significantly by extracting temporal features. However, as the number of training anomalies decreases, the improvement becomes less substantial.

Table 4. Performance criteria comparisons of FCDD and FCDD-GRU-Att.

Training Portion (Nor:Ano)	Training Anomalies Number	Prec(%)		Detec(%)		FA(%)	
		FCDD	FCDD-GRU -Att↑	FCDD	FCDD-GRU -Att↑	FCDD	FCDD-GRU -Att↓
1.96:1	840 (28 seq)	92.36	98.46 (↑6.1)	85.2	96.15 (↑10.9)	2.91	0 (↓2.91)
2.75:1	600 (20 seq)	86.15	93.85 (↑7.7)	71.41	88.46 (↑17.05)	4.02	2.56 (↓1.46)
3.43:1	480 (16 seq)	87.18	90.77 (↑3.59)	71.03	88.46 (↑17.43)	2.05	7.69 (↓5.64)
4.58:1	360 (12 seq)	86.26	87.69 (↑1.43)	70.26	84.62 (↑14.36)	6.16	10.26 (↓4.1)

Frame numbers of sequence: It is evident that frame number makes a difference in temporal feature extraction. Therefore, in this subsection, we explore the influence of frame number in the proposed sequential anomaly detection algorithm. Moreover, we expand the dataset above to ensure a more valid evaluation. A training dataset with 10,740 images is constructed by incorporating different oriented attitudes, with 6540 images in normal shapes and the rest being anomalies. The testing dataset has been expanded as well, with 2700 normal images and 3000 anomalies. There are 30 sequences for a circle. To evaluate the influence of frame number, sequences are constructed with 30, 15, 10, 5, 3, and 1 frames per sequence. The precision, detection rates, and false alarm rates are also calculated for an overall evaluation, as shown in Figure 14. It is evident that the improvement of sequential features increases with longer sequences. However, even with 3 frames per sequence, the detection rates have been improved by exploiting the context of sequential ISAR images. To achieve 100% detection and a low false alarm rate of <2%, 15 frames per sequence are recommended. For 5 frames per sequence, the proposal can achieve anomaly detection rates >99% with an FA of almost 3%.

**Figure 14.** Anomaly score statistics. (a) Anomaly score histograms; (b) False alarm rates of different targets.

SNR: By adding random Gaussian-distributed noise to the simulated testing dataset above, different ISAR image sequences at varying SNRs are generated. The criteria Prec, Detec, and FA are then used to evaluate the proposal's performance at different SNRs during testing, as shown in Figure 15. Monte Carlo experiments are performed ten times for each SNR, and the mean values of the criteria are drawn. For comparison, the original FCDD is also performed.

As demonstrated, the temporal context can significantly improve the original FCDD's detection precision and false alarm rates. The proposal can deliver an accessible performance even under SNR = 0 dB. When the SNR decreases further, the improvement is minimal. That may be because the skeleton-related geometrical features in ISAR images are blurred.

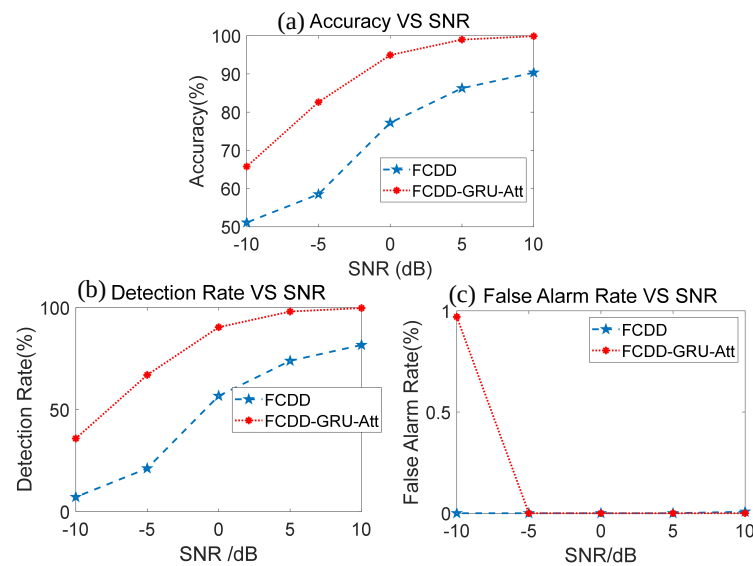


Figure 15. Performance vs. SNR: (a) Accuracy; (b) Detection rate; (c) False alarm rate.

4.5. Comparisons

To validate the superiority of our proposal, we compare it to available methods such as the isolation forest [18], OCSVM [42], FCDD [33], and Vision Transformer (Vit) of binary classification [43]. As stated above, Prec, Detec, and FA are evaluation criteria for anomaly detection. For simplicity, we feed flattened $A(X)$ generated by FCDD as features for the isolation forest and OCSVM-based anomaly detection since they do not have the capability to extract spatial features from images.

As illustrated in Table 5, the proposal outperforms existing methods in terms of detection rates and overall precision. Since we incorporate temporal context information into the explainable FCDD network for anomaly detection, the proposal may take advantage of both spatial and temporal features, promising high detection rates.

Table 5. Performance comparisons.

Structures	Criteria	Prec (%)	Detec (%)	FA (%)
Isolation Forest		66.930	46.27	10.11
OCSVM		79.649	68.48	0.33
FCDD		92.3	95.77	0.19
Vit		88.509	92.03	15.4
FCDD-Att-GRU		99.474	100	1.11

To our knowledge, existing anomaly detection systems address either a single image or a feature flow independently. However, in many cases, such as ISAR imaging of space targets, sequential observations are typically generated to monitor and evaluate targets. Moreover, unexpected shape anomalies occur and cannot be self-recited in short intervals without human intervention. In this way, sequential ISAR images can be utilized for shape anomaly detection improvement by leveraging both spatial and temporal features.

However, in order to detect shape anomalies, we are interested in both the occurrence and location of form anomalies. The FCDD network not only provides comparable anomaly detection capability as state-of-the-art methods, but it can also generate explainable heatmaps to locate the anomalous parts. Therefore, we employ an FCDD network to extract spatial features linked to shape anomalies. It anticipates significant performance in

spatial–temporal anomaly identification for satellites using ISAR picture sequences when combined with a temporal information extraction architecture.

5. Discussion

The results demonstrate that the proposed explainable framework effectively detects and localizes shape anomalies of space targets from ISAR image sequences, outperforming existing methods in both interpretability and detection accuracy. Compared with the traditional downsampling of abnormal heatmaps through FCDD networks, our method proposes a joint approach with an attention-based GRU architecture, introducing the joint of temporal and spatial features to achieve interpretable shape anomaly detection based on ISAR image sequences, improving the solution of detecting and locating anomalies simultaneously. Compared with the traditional downsampling of abnormal heatmaps through FCDD networks, our method proposes a joint approach with an attention-based GRU architecture, introducing the joint of temporal and spatial features to achieve interpretable shape anomaly detection based on ISAR image sequences, improving the solution of detecting and locating anomalies simultaneously.

These findings validate the working hypothesis that ISAR geometric projections encode sufficient structural information for identifying physical anomalies such as panel folding or component loss. The study also shows that our approach can not only display the differences between abnormal images and normal images, but also accurately locate the abnormal parts in ISAR images.

From a broader perspective, this study provides new ideas for intelligent space situational awareness, making satellite health monitoring more reliable, interpretable, and data-efficient, as well as addressing the lack of public research on satellite shape anomalies. Future work will expand this method to handle more complex non-rigid deformations, as well as to further improve the model's generalization and practical robustness.

6. Conclusions

In this paper, we propose a sequential, explainable shape anomaly detection method for satellites using sequential ISAR images. Because of the temporal nature of satellite shape anomalies, temporal context can be utilized to improve shape anomaly detection. Therefore, we begin by utilizing a traditional FCDD network to extract spatial features associated with anomalies. Then, a GRU-Att-based architecture is followed to extract temporal relations between the spatial features. By incorporating both temporal and spatial information, the detection of shape anomalies can be significantly improved. The experimental results validate the effectiveness and superiority of the proposal. This experiment uses six types of satellites to verify the generalization of the method. Moreover, the proposal can give explainable heatmaps to locate the anomalies for better understanding and further human judgments. The explainability of the results stems from the physical correspondence between the detected ISAR anomalies and the target's geometric structure.

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Abbreviations

The following abbreviations are used in this manuscript:

ISAR	Inverse Synthetic Aperture Radar
FCDD	Fully Convolutional Data Description
AD	Anomaly Detection
GMM	Gaussian Mixture Model
LOS	Light Of Sight
FCN	Fully Convolutional Description
HSC	Hypersphere Classifier

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